Vibration based Assessment of Tool Wear in Hard Turning using Wavelet Packet Transform and Neural Networks

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Abstract: Demanding high dimensional accuracy of finished work pieces and reducing the scrap and production cost, call for devising reliable tool condition monitoring system in machining processes. In this paper, a tool wear monitoring system for tool state evaluation during hard turning of AISI D2 is proposed. The method is based on the use of wavelet packet transform for extracting features from vibration signals, followed by neural network for associating the root mean square values of extracted features with tool flank wear values of the cutting tool. From the result of performed experiments, coefficient of determination and root mean square error for the proposed tool wear monitoring system were found to be 99% and 0.0104 respectively. The experimental results show that wavelet packet transform of vibration signals obtained from the cutting tool has high accuracy in tool wear monitoring. Furthermore, the proposed neural network has the acceptable ability in generalizing the system characteristics by predicting values close to the actual measured ones even for the cutting conditions not encountered in the training stage.

Keywords: Hard Turning, Neural Networks, Tool Wear Monitoring, Vibration Signals, Wavelet Packet Transform

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1 INTRODUCTION

Hard turning is described as the turning process of work pieces that have hardness values over 45 HRC. This process, which is aimed for finish machining of a wide range of hardened steel work pieces, enables manufacturers to simplify their processes and still achieve the desirable surface finish quality. Its advantages in terms of the increased flexibility of the manufacturing technology, relatively acceptable rate of material removal, and better environmental aspects make it an undeniably economical manufacturing process [1]. One of the most important issues that must be considered in hard turning is cutting tool wear. The state of tool wear is a vital factor directly affecting the surface quality and dimensional accuracy of the parts being manufactured [2]. Therefore, tool wear monitoring (TWM) is inevitable to reduce machine tool downtime and to maintain the desired dimensionality and surface finish [3]. TWM methods can be categorized into two classes: direct and indirect methods. Direct methods are based upon direct measurements of the tool wear by using optical instruments [4], radioactive [5], electrical resistance methods [6] or vision systems [7], etc. Although these methods present the advantage of high accuracy, they have not yet shown to be either economical or technical method of monitoring. Indirect methods are based on the relationship between cutting tool condition and measurable signals that are obtained from the cutting process. This involves measuring process parameters which are correlated with wear such as force [8], vibration [9], acoustic emission [10], cutting temperature [11], etc. Even though these methods offer ease of measurement and are economical compared to direct methods, very few reliable indirect methods have been established for industrial applications. This is mainly because of the nonlinear relationship between the measured features and tool wear [12]. Among the mentioned TWM techniques, the use of vibration signals has received wide popularity because of fast data collection and accurate interpretation ability [13]. Accelerometers or vibration sensors offer some extra advantages over other sensing techniques such as ease of implementation and the fact that no modifications to the machine tool or the work piece fixtures are required [14]. Vibrations are created by variations in the dynamic and static components of the cutting forces [15]. Mechanical vibrations result from the tool wear and the cutting conditions have periodic nature and a very minimum vibration from the machine tool and shop floor are also incorporated in resultant vibration signal [16].

In the field of TWM by vibration signals, Segreto et al., used a multiple sensory system to perform TWM in the turning process of a nickel alloy. Dynamometer, acoustic emission (AE) sensor and accelerometer were used for monitoring signals [17]. Salgado et al. by using variant signals obtained from an accelerometer and feed motor current tried to determine the value of flank wear when cutting aluminum and steel by singular spectrum analyze [18]. Painuli et al. in their research considered k-star classifier to correlate cutting the tool condition to vibration signal of tool holder. Considering the results obtained from experiments showed that the accuracy of the proposed methodology was 78% for classifying the tool state [19]. Aghdam et al. using ARMA technique, modeled vibration signals of the tool in turning the process to make a relation between the dynamics of tool/holder system and the tool major flank wear [20]. Wang et al. employed dynamometer and accelerometer to monitor the tool state in the milling process. Proposed method improved the effectiveness of sensing capability by using various dimension reduction techniques [21]. The main problem that researchers are faced with in achieving to an effective TWM system is the nonlinear and variant nature of the cutting process versus time. The variation in the measured signals which is because of different disturbances is another problem which must be considered. Usually it is hard to determine whether the source of this variation in the signals is due to tool wear or a change in the cutting conditions or machine abnormality [22]. Hence, the measurement of signals is not as difficult as interpreting them for the correct tool wear state prediction. Signal processing is carried out to increase the level of information contents of the signals and eliminate the disturbing influences [23]. Usually signal processing and feature extraction approach should be used to make the vibration signal more beneficial in TWM. During the feature extraction stage, the most appropriate features that correlate well with tool wear are extracted from the prepared signals. Features are usually derived from any of the time, frequency, time-frequency, or statistical domain. Successful use of time-frequency domain features for TWM has been demonstrated in few publications. The feature extraction in the time-frequency domain is mostly performed with the use of wavelet transform. Wavelet transform provides information about localization of a signal in the time domain and the frequency domain at the same time. Feature extraction with wavelet transform reduces the processing time [23]. Furthermore, because of its fault dependent property, wavelet packet transform (WPT) can be utilized in signal processing widely and this ability facilitates the effectiveness of this useful technique [24]. Using wavelet transform in TWM has been well explored by researchers and many works have been published. Wu and Du [25], based on the WPT and signal reconstruction, introduced a new feature extraction method. To assess the effectiveness of the selected features in time and frequency domains, various criteria were proposed. Accordingly, an automatic feature extraction procedure was developed. The proposed method was tested in drilling and results showed the accuracy of method. Xiaoli and Zhejun [26] investigated TWM in the boring and milling process using WPT and fuzzy clustering method for generating features from AE signals with more correlation with tool flank wear. Mehrabi et al. [27] considered the discrete wavelet transform for feature extraction from vibration signals. Scheffer et al. [28] used the wavelet transform with spectrograms in order to identify the most stationary parts of force signals for frequency domain analysis. Velayudham et al. [29] studied the capability of WPT in the characterization of the acoustic emission signals released from glass polymeric composite during drilling. Zhu et al. [30] performed a detailed review of different applications of wavelet analysis in TWM techniques and showed that wavelet transform is more effective in analyzing nonstationary machining sensor signals than any other signal processing method. Chen et al. [31] considered wavelet filtering while Lee [32] used wavelet for processing of vibration and AE signals. Classifiers play a vital role in tool condition monitoring systems. Neural network classifiers seem to be a popular choice among the researchers due to its useful abilities such as high rate of adaptability and good prediction accuracy [23]. Application of neural networks in TWM has been reported by some researchers such as Mikołajczyk et al. [33], Teshima et al. [34], Ghosh et al. [8], and Kaya et al. [35]. Hard turning is considered a cost-effective alternative to other finishing processes such as grinding. Because of the negative effect of tool wear on surface roughness, the wear monitoring of cutting tool is of great importance in hard turning. Despite previous research effort, no relevant research has been reported in the field of tool wear monitoring in hard turning process. On the other hand, in the majority of performed researches, no detailed analysis is presented about the frequency bands in which the effect of tool wear can be traced. Another important problem of previous researches is the expensive sensory system, which makes proposed monitoring systems economically unjustifiable.

Due to the drawbacks of these commonly performed researches, there is a need to develop an efficient, easy to use, low-cost and precise technique for progressive monitoring of tool flank wear in hard turning. In this research, an online tool wear monitoring system is proposed based on WPT of vibration signals and neural networks in hard turning of AISI D2. To make the monitoring system drastically cost-effective, the one-directional accelerometer was used. The vibration is measured in machining direction since this direction has more dominant signals than the other two directions. The measurements are taken by using an acceleration sensor assembled on a tool holder. WPT of vibration signals is used to decompose the primary prepared signals and obtain a set of features. Among the composed features, the most correlated signals with tool condition are extracted. The RMSs of the wavelet coefficient of the extracted signals are fed to neural networks as input. The output of the trained neural network is tool flank wear. The paper is organized as follows: section 2 is a theoretical background of wavelet transforms. Section 3 explains the experimental setup. In Section 4 the results of experiments will be represented and discussed. Section 5 contains the conclusion.

2 SIGNAL ANALYZING USING WAVELET PACKET TRANSFORM

2.1. Wavelet Transform

It is known that an energy limited of a signal *f(t)*, can be decomposed by its Fourier transform *F(ω)* as:

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} F(\omega)e^{-i\omega t}d\omega \tag{1}$$

$$F(\omega) = \int_{-\infty}^{+\infty} f(t)e^{-i\omega t}dt \tag{2}$$

Note that *F(ω)* and *f(t)* constitute a pair of Fourier transforms. Equation (2) is called the Fourier transform of *f(t)* and equation (1) is called inverse the Fourier transform. From a mathematical point of view, equation (1) implies that the signal *f(t)* can be decomposed into a group of harmonics e^{iwt} and the weighting coefficients *F(ω)* represent the amplitudes of the harmonics in *f(t)* [25].

The wavelet transform is defined similarly with some slight changes. However, instead of using the harmonics e^{iwt}, the wavelet transform uses wavelet bases:

$$\psi_{st}(t) = \frac{1}{s}\psi(\frac{t-\tau}{s}) \tag{3}$$

In which *s* represents the frequency, τ represents the time shift, and *ψ(0)* is named a mother wavelet function. In a similar way, a signal *f(t)* can be decomposed into:

$$\mathrm{f(t)} = \frac{1}{\mathrm{c_\psi}}\int_{-\infty}^{+\infty}\int_{0}^{+\infty} W_s[f(\tau)]\frac{1}{s}\psi\left(\frac{t-\tau}{s}\right)dsd\tau \tag{4}$$

Which c_ψ is a constant depending on the base function, and $W_s[f(t)]$ is the wavelet transform defined below:

$$W_s[f(\tau)] = \int_{-\infty}^{+\infty} f(t)\frac{1}{s}\psi\left(\frac{t-\tau}{s}\right)dt \tag{5}$$

Similar to the Fourier transform, $W_s[f(t)]$ and *f(t)* constitute a pair of wavelet transforms. Specially, equation (5) is called the wavelet transform of *f(t)* and equation (4) is called the inverse wavelet transform [25]. In comparison with the Fourier transform, equation (4) shows that wavelet transform can be considered as the signal decomposition. It decomposes a signal *f(t)* into a family of wavelet bases, and the weighting coefficients, $W_s[f(t)]$, represent the amplitudes at a given location (τ) and frequency (s). Compared to the Fourier transform, the wavelet transform is a time-frequency function which characterizes the behavior of *f(t)* in different time windows and frequency bands. WT presents a three-dimensional figure versus the time-frequency plane. On the contrary, the Fourier transform *F(ω)* depends only on frequency and hence, forms a two-dimensional curve versus the frequency axis.

As a result, the wavelet transform is capable of capturing non-stationary information such as frequency variation and magnitude undulation, whereas the Fourier transform does not have mentioned ability [25].

2.2. Wavelet Packet Transform

The WPT method is a generalization of the wavelet decomposition that offers a rich range of possibilities for signal processing and analysis [36]. Wavelet packet decomposition split the original signal S into two frequency bands: an approximation A and a detail D. The approximation A is then itself split into a 2nd level approximation AA and detail AD, the detail D is split into a 2nd level approximation DA and detail DD, and the process can be repeated for the 3rd level and over. The schematic view of this process is shown in “Fig. 1”. For an *n*th level decomposition, the signal can be decomposed in *n+1* possible ways [37]. For example, wavelet packet analysis allows signal S to be represented as a summation of packets such as: A + AAD + DAD + DD that cover all branches of the decomposition packets tree. Each packet is composed of $N\times2^{-j}$ coefficients defined as:

$$A_{j+1}[n] = \sum_{k=-\infty}^{+\infty} h[2n-k]A_j[k] \tag{6}$$

$$D_{j+1}[n] = \sum_{k=-\infty}^{+\infty} g[2n-k]D_j[k] \tag{7}$$

In which:
N: number of original signal samples,
j: number of transformation levels with $j = 1, 2, \ldots,$
k: number of filter coefficients,
n: number of packet coefficients with $n = 1, 2, \ldots, N\times2^{-j}$,
g: coefficients of high-pass filter,
h: coefficients of low-pass filter based on chosen mother wavelet [38].

3 EXPERIMENTATION

The main scheme of the experimental procedure for the online TWM system is designing a system to evaluate flank wear values as accurately as possible for hard turning of AISI D2. The experiments were performed on an Emcoturn CNC lathe machine. The work piece was a round bar (60 mm diameter and 250 mm long) AISI D2 alloy steel with hardness 46 HRC. The TiN coated carbide insert, type TNMG 220408 with grade NC3030 was selected. The experiments were conducted in dry cutting mode.

The cutting parameters were: cutting speed (*v*) 40, 60, and 80 m/min, and feed rate (*f*) 0.02, 0.04, and 0.06 mm/rev. Since the process had been designed for finish turning, the depth of cut was selected 1 mm. For each cutting condition, 12 tests were performed in various cutting times in order to investigate the effect of cutting parameters along with tool wear on vibration signals. Therefore, 108 cutting tests totally were carried on until tool life end. Maximum tool life (VB_{max}) was considered 0.3 mm.

All vibration signals were captured using a CTC AC102 accelerometer with a sensitivity of 100±5% mV/g, which had been mounted on the holder as near as possible to insert. The frequency range of measurement was 1 Hz to 5 kHz. The accelerometer was connected to a CTC signal conditioner, which was powered by a 10V supplier. A NI USB DAQ 6008 data acquisition card with a sampling rate of 10 kHz was selected. The captured signals were passed through this data acquisition to MATLAB software for further processing and signal display. Figure 2 shows a schematic representation of the equipment set-up.

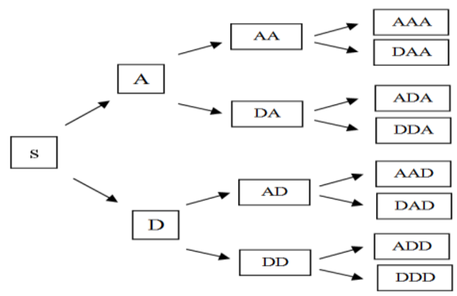

Fig. 1 Three level wavelet packet decomposition [38].

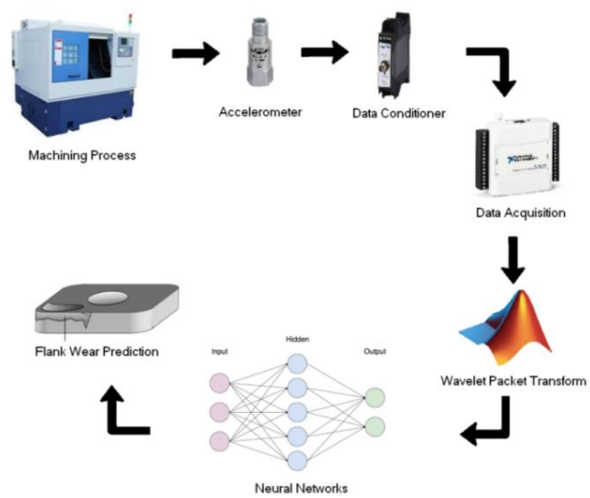

Fig. 2 Schematic diagram of the experimental set-up.

As illustrated, vibration signals are collected by an accelerometer. These signals are amplified by a signal conditioner and are sent to the WPT unit through a data acquisition card. In “Fig. 3”, experimental set-up of the study is shown.

The collected vibration signals were subjected to processing in the time-frequency domain by four levels WPT. The RMSs of the wavelet coefficient of the decomposed signals were calculated and then were sent to the neural network. Input parameters of the neural network were cutting speed, feed rate and RMSs of wavelet coefficient of selected features, which have the most correlation with tool wear values. Output was tool wear values. The trained network had 3 layers with 10 neurons in each hidden layer.

Fig. 3 Experimental set-up used in the present study.

A schematic view of the trained neural network is shown in “Fig. 4”. The Levenberg-Marquardt training algorithm was used to train the feed-forward back propagation network in this research. A light source microscope with magnification 36x and image processing software were employed respectively to capture the image of corresponding flank wear and make measurements of wear values.

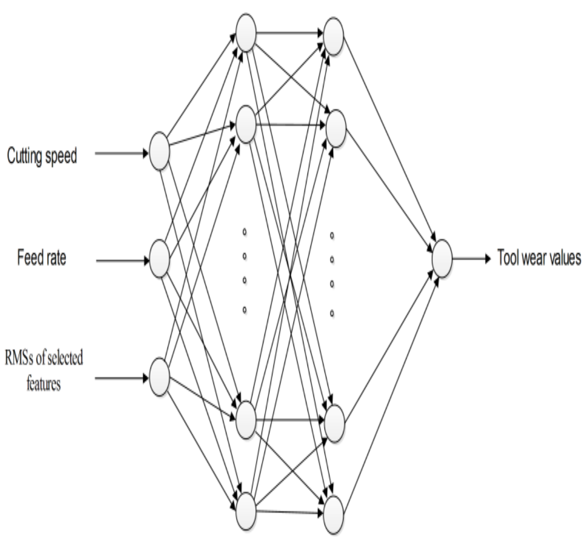

Fig. 4 A schematic view of the trained neural network.

4 RESULTS AND DISCUSSION

4.1. Signal Analysis

After performing specified cutting tests, according to cutting parameters mentioned in experimentation, vibration signals were captured and tool flank wear values were measured carefully.

Figure 5 displays original vibration signals captured in different flank wear values in the time domain when machining with *v*=60 m/min and *f*= 0.04.

At the beginning moments of the cutting process, the tool was fresh (VB=0.06 mm), therefore the magnitude of the original signal was small (“Fig. (a)”). As the tool wear increased (VB=0.137mm), the magnitude of the original signal changed (“Fig. 5(b)”).

In the end moments of tool life (VB=0.27mm), the high magnitude for vibration signal was evaluated (“Fig. 5(c)”). Considering the original signals corresponding to VB=0.06 mm, VB=0.137 mm, and VB=0.27 mm, it can be found that the magnitude of the original signal increased as the tool flank wear expanded.

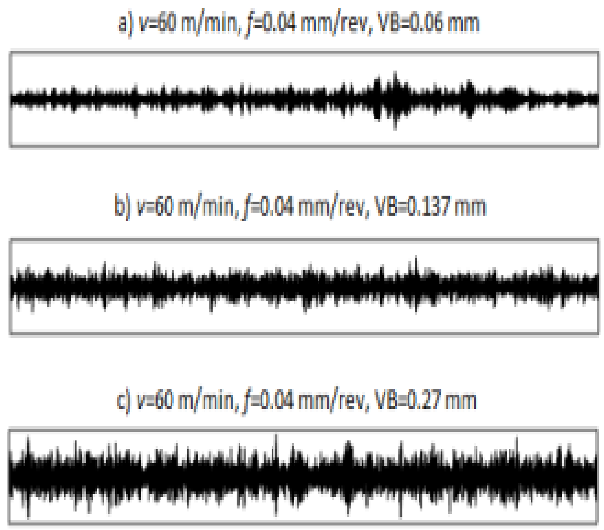

Fig. 5 Captured signals v= 60 m/min and f= 0.04 mm/rev for different tool flank wear values: (a): VB=0.06 mm, (b): VB=0.137 mm and (c): VB=0.27 mm.

Figure 6 shows the decomposing results of vibration signal for *v*=60 m/min and *f*= 0.04 when VB=0.27 mm. The decomposed components of the original signal are listed from n1 to n16 which each component corresponds to a specific frequency band from [0, 312.5] Hz to [4687.5, 5000] Hz respectively.

4.2. Feature Extraction

In vibration based TWM systems, monitored signals contain some environmentally affected information. To ensure the reliability and robustness of TWM, extracting the features of the signal that describe the tool condition is necessary. Therefore, utmost care must be taken in selecting the features that have the most correlation with tool flank wear. The selected sub-band features must describe the overall condition of the system independently and their number must be large enough.

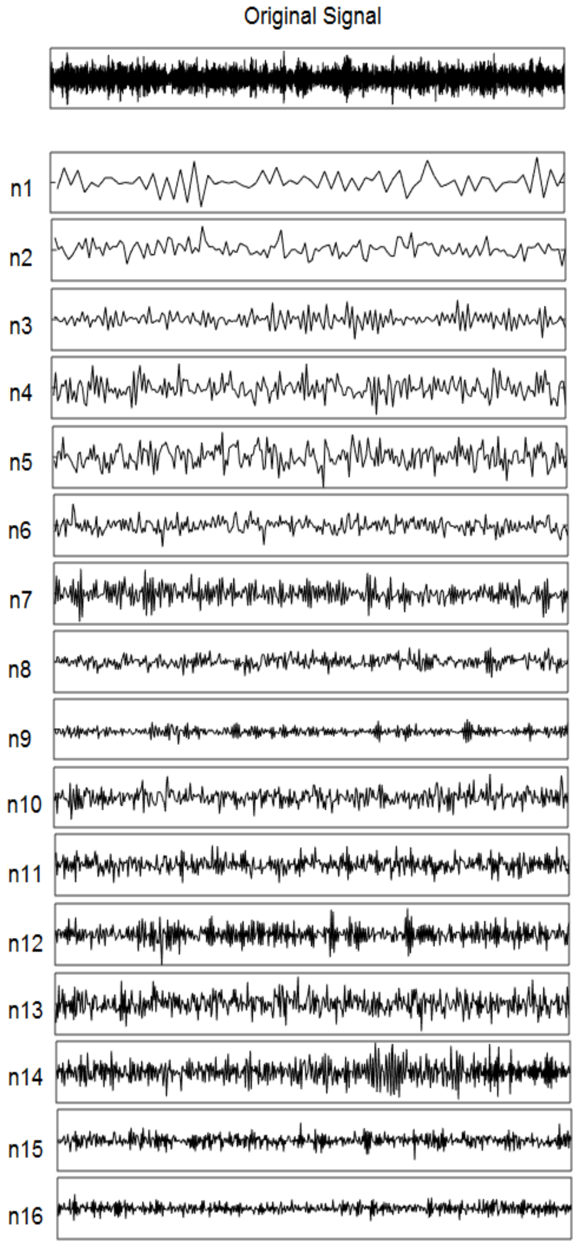

Fig. 6 Captured signal for v= 60 m/min and f= 0.04 mm/rev and decomposed wavelet packets, VB=0.27 mm.

Using wavelet packet transform, each of 108 raw vibration signals was decomposed into 4 levels consisting of 16 sub-band components and the corresponding RMS values of wavelet coefficients were calculated. Each wavelet packet corresponded to each frequency band ranging from [0-312.5] Hz to [4687.5-5000] Hz. By precise consideration of RMS values of sub-band components, it was found that the effect of tool gradual wear can be traced in only 4 decomposed signals; 2nd, 6th, 11th and 14th sub-band signals. These features corresponded to [312.5-625] Hz, [1562.5-1875] Hz, [3125-3437.5] Hz and [4062.5-4375] Hz frequency ranges respectively.

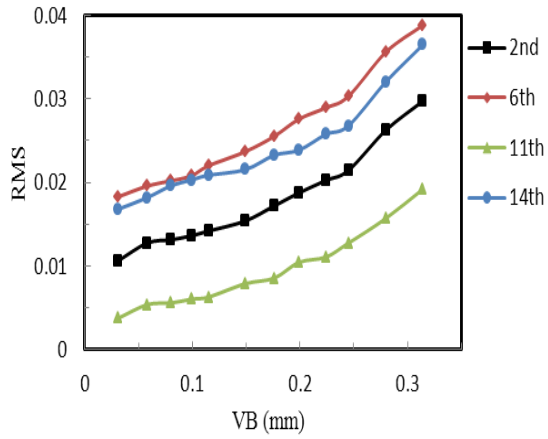

Fig. 7 RMS of wavelet coefficients in selected features for v=60 m/min and f=0.02 mm/rev.

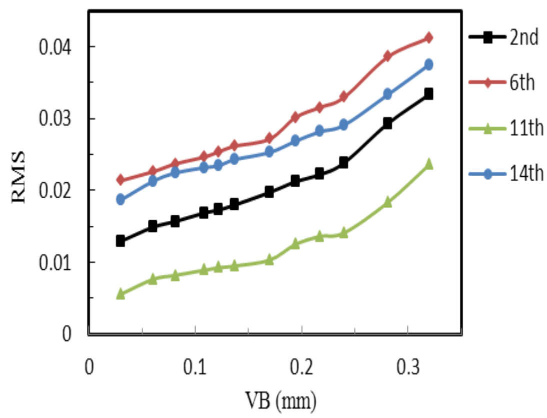

Fig. 8 RMS of wavelet coefficients in selected features for v=60 m/min and f=0.04 mm/rev.

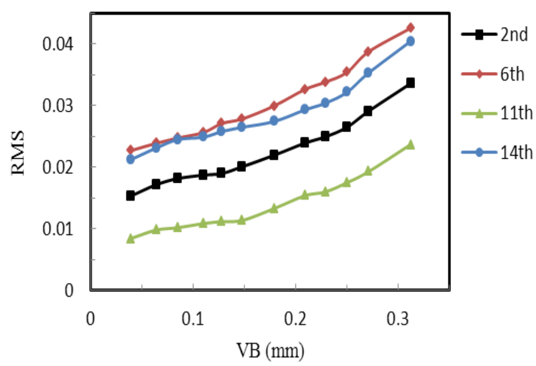

Fig. 9 RMS of wavelet coefficients in selected features for v=60 m/min and f=0.06 mm/rev.

The variation of RMS of wavelet coefficients in mentioned frequency ranges for cutting speed 60 m/min and feed rates 0.02, 0.04 and 0.06 mm/rev are represented in "Figs. 7-9". As can be seen, in all selected features, the value of RMSs increases with any increase in tool wear values. The increase in the RMSs along with gradual tool flank wear is an indicator of the correctness of selected sub-band features. However, such a manner was not observed in other decomposed features with different frequency bands. Since the effect of cutting parameters will be reflected by the extracted features, the cardinal part of the TWM system is assessing the effect of cutting parameters on the selected features, [26]. It is evident that the selected features are sensitive to any variation in cutting speed and feed rate. Results of previously performed studies have indicated the correlation between cutting force and machining vibration signal.

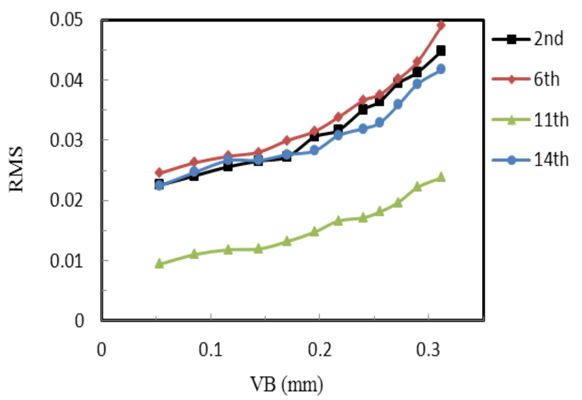

Fig. 10 RMS of wavelet coefficients in selected features for v=80 m/min and f=0.06 mm/rev.

Any increase in cutting force usually accompanies with the increase in vibration captured from tool holder in machining [39]. Figures 7, 8, and 9 indicate that an increase in feed rate causes the RMSs to increase. The reason for this change can be explained by the variation of undeformed chip thickness. Increasing the feed rate caused undeformed chip thickness to increase that resulted in a noticeable rise in cutting forces and subsequently led to increscent of vibrations. The variation of RMSs of wavelet coefficients of selected features for cutting speeds 80 m/min and feed rate 0.06 mm/rev is demonstrated in "Fig. 10". Considering the behavior of RMS values shown in "Fig. 9" and "Fig. 10", it was found that the effect of the increase in cutting speed could be seen only in features with low frequency band. The main reason is the negligible effect of cutting speed on cutting force in turning of hardened AISI D2 [40]. Therefore, only a little increase was encountered in low frequency features (n1 and n2), which was because of natural increased vibration magnitude in machine tool in higher spindle rotations.

4.3. Neural Networks

In this research a three-layer feed forward network was structured to predict the tool flank wear. Input parameters of the network were cutting speed, feed rate and the RMSs of wavelet coefficient of the decomposed vibration signals. To train the neural network, 100 tests were used according to mentioned cutting parameters discussed in the experimental section. "Table 1" shows the selected tests to validate the proposed monitoring system. Validation tests were not presented to the network for training and were used only for evaluating the accuracy and reliability of the proposed monitoring system.

Table 1 Experimental validation tests

			RMS of selected features					Flank wear VB (mm)	
Test No.	Cutting speed (m/min)	Feed rate (mm/rev)	2nd	6th	11th	14th		Measured	Predicted
1	40	0.04	0.0194	0.0389	0.0195	0.0361		0.288	0.264
2	60	0.02	0.0265	0.0363	0.0188	0.0318		0.314	0.328
3	60	0.04	0.0169	0.0247	0.0099	0.0252		0.137	0.157
4	80	0.02	0.0269	0.0280	0.0111	0.0249		0.221	0.194
5	40	0.035	0.0017	0.052	0.0255	0.0305		0.271	0.250
6	50	0.05	0.0085	0.029	0.0098	0.0249		0.132	0.121
7	70	0.03	0.024	0.028	0.0126	0.026		0.19	0.201
8	85	0.06	0.0253	0.0281	0.0131	0.0291		0.126	0.144
9	40	0.04	0.0079	0.0241	0.0089	0.0229		0.143	0.153
10	60	0.02	0.0136	0.0208	0.0061	0.0203		0.099	0.112
11	60	0.06	0.022	0.03	0.0133	0.0274		0.179	0.191
12	80	0.04	0.0322	0.0327	0.0158	0.0302		0.242	0.223

The values of input cutting parameters along with measured and predicted wear values of validation cutting parameters and corresponding RMS values of wavelet coefficients of selected features are shown in "Table 1". The accuracy of the trained network in this research was evaluated in terms of two statistical measures. These measures were the root mean square error, *RMSE*, and coefficient of determination, R^2, which are defined as below:

$$RMSE = \sqrt{\sum_{m=1}^{n} \frac{(Y_{predicted,m} - Y_{experimental,m})^2}{n}} \quad (8)$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(Y_{predicted,m} - Y_{experimental,m})^2}{\sum_{m=1}^{n}(Y_{experimental,m})^2} \quad 9)$$

Where n is the number of data points, *Ypredicted,m* and *Yexperimental,m* indicates the predicted value and the measured value from experimental data, respectively, of one data point *m*. *RMSE* gives the deviation between the experimental and predicted values. A precise fit yields R^2 value of 1, whereas a poor fit results in a value near zero. Based on values obtained for *RMSE* and R^2, the accuracy of the trained network for both train and validation data set was evaluated as shown in “Table 2”.

Table 2 Fitness values of trained neural network

	R^2	*RMSE*
Training	0.9934	0.0104
validation	0.9511	0.0261

The results given in “Table 2” allow concluding that proposed TWM methodology has a unique ability in assessing the value of flank wear in finish turning of AISI D2. Furthermore, the system has good prospects in predicting tool flank wear for cutting parameters other than those in the training set.

6 CONCLUSION AND FUTURE WORK

One of the most difficult problems in TWM is extracting signal features and describing the correlation between extracted features and tool wear values as accurate as possible. Based on the wavelet packet transform, an efficient system for TWM was designed. Key features were extracted from vibration signals. These features were used as input of a neural network, which was trained to predict tool flank wear. The proposed technique can be integrated into an industrial tool condition monitoring system and estimate the value of tool flank wear at various cutting conditions quite accurately in real time.

The results can be summarized as follows:

1- In order to design a reliable and applicable TWM system, vibration signals can be used. Furthermore, using a vibration sensor offers some extra advantages over other sensing techniques such as ease of implementation and the fact that no modifications to the machine tool or the work piece fixtures are required.

2- The WPT has an acceptable performance and high accuracy in TWM. This technique has the ability to capture the important features of sensor signal that are sensitive to tool flank wear. Therefore, reliable and accurate online monitoring decisions can be made. Moreover, the RMS of the wavelet coefficient of selected features contains important information about tool condition and can be considered as the monitoring factor of features.

3- Results show the ability of the proposed neural network in generalizing the system characteristics by predicting values close to the actual measured ones even for the cutting conditions not encountered in its training stage.

In the authors’ opinion, researches in TWM systems should center in the future on preprocessing signals obtained from more sensors that work together. Moreover, it is proposed to perform precise cutting parameters and develop time-frequency signal processing techniques, such as wavelet transforms, to get more information about the different frequency bands that the various sources of noise, for example machine tool parts, generate.

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